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***Abstract* - In this paper, we propose an automated method to assess wall motion in Left Ventricle (LV) function in cardiac cine-Magnetic Resonance Imaging (MRI) based on Dictionary Learning (DL) classification with a parametric approach. Time-signal intensity curves (TSICs) are identified in spatio-temporal profiles extracted from differents anatomical segments in a cardiac MRI study. Parameters are extracted from TSICs that present a decreasing then increasing shape reflecting dynamic information of the LV contraction. Several parameter combinations are used as input atoms to train a sparse classifier based on kernel DL and results are compared with Support Vector Machines. Best classification performance is obtained with an accuracy about 94%.**

***Index Terms* - Image Processing, Magnetic Resonance Imaging, Medical Informatics**

I. INTRODUCTION

Several approaches for quantitative evaluation of LV regional wall motion have been proposed in the literature.In particular, Caiani *et.al* [1], used parametric images of the dynamic loops of cardiac MR images to improve the accuracy and reduces the interobserver variability of the detection of regional wall motion abnormalities by non-cardiologists. Parametric analysis of LV motion was also presented by Kachenoura *et.al* [2] in cine MR images for the evaluation of regional myocardial function with the extraction of segmental parameters related to mean contraction times and mean radial velocities. In our previous work [3], diametral spatio-temporal profiles are extracted from sequences in short-axis cardiac cine-MRI. The profile gray level information and its representation in the wavelet domain are used as features to train classifiers based on discriminative Dictionary Learning (DL) and Support Vector Machines (SVM) to determine whether a segment presents LV wall motion abnormality. In this paper, we propose a DL-based classification with a parametric approach to assess wall motion in LV function based on time-signal intensity curves (TSICs) that are extracted from radial spatio-temporal profiles. These curves show dynamic information of LV contraction based on pixel intensity values in the cardiac cavity. The parameters obtained from the TSICs are related to: 1) mean transition times, 2) curve skewness, 3) an average curve based on a clustering process and 4) cross correlation values between each TSIC and a patient-specific reference. These parameters are used to train a classifier based on kernel DL. Results are compared with SVM using a RBF kernel.

II. MATERIALS AND METHODS

II.1. Population and Image Acquisition

Short-axis cardiac cine-MR images are collected from 9 patients with cardiac dyssynchrony and from 9 healthy subjects. Spatio-temporal profiles (Figure 1, left) are obtained following the procedure in [3] for radial profiles extracted from the LV centroid to a point outside of the epicardial border in the LV cavity. For each patient we extract a set of $I^M \in \mathbb{R}^{40\times 20}$, radial spatio-temporal profiles in the medial plane, where $M \in \{1,\ldots,360\}$, each associated with a profile orientation in the 360° scans of the LV. In Figure 1-middle, three types of TSICs, $C(x,y,t)$ associated with the pixel $c(x,y)$ are observed. Green color is assigned to the pixel points that remain within the myocardium during the whole cardiac cycle and to the pixels that remain inside the cavity. Red color labels the pixels from curves that present a decreasing then increasing shape. Blue color is assigned to the pixels from curves that present an increasing then decreasing shape with low amplitude. A gaussian function $f(t)$, (Figure 1-right), is fitted to each inverted TSIC that presents a decreasing then increasing shape using an iterative Least-Mean-Square (LMS) algorithm, then we calculate different parameters.

II.2. Parameters from time-signal intensity curves

Mean transition times (Mt) are computed following the procedure described in [2], *i.e.*, we calculate the average of the transition times parameters $TON(c)$ (time when the contraction begins) and $TOFF(c)$ (end of the endocardial movement) obtained from the fitted TSIC. An average curve based on a clustering process (Cl) is calculated from the fitted TSICs in sub-regions of ten consecutive profiles in the LV cavity. A multisignal 1-D clustering process

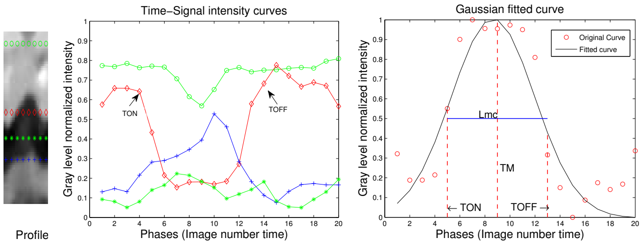

Figure 1: TSICs from a spatio-temporal profile

splits the set of TSICs into two clusters, then the average of the signals in the largest cluster is computed representing the largest group of signals with a similar contraction pattern. A skewness parameter (Sk) is computed from 5 random TSICs selected in the profiles from a particular sub-region. Negative skewness reflects late regional LV contraction and positive skewness reflects early regional LV contraction. A parameter based on cross-correlation analysis (Co) is calculated between each fitted TSICs and a patient-specific reference. To define this reference we perform a global multisignal 1-D clustering overall the TSICs from the profiles that belong to the control subjects. The average of the cluster with maximum size is a patient-specific reference from the healthy population.

II.3. **Dictionary-learning-based classification**

We aim at classifying whether a segment presents LV wall motion abnormality or not using parameters extracted from TSICs in the profiles. To this end, we apply a DL approach for classification based on kernels (KSRDL). The KSRDL algorithm [4] uses different priors on the sparse coefficient vector $\boldsymbol{Y}$ from the input signals $\boldsymbol{D}$, and the dictionary $\boldsymbol{A}$, which lead to various sparse representation models, e.g. Gaussian prior (1):

$$\min_{\boldsymbol{A},\boldsymbol{Y}} \frac{1}{2}\|\boldsymbol{D}-\boldsymbol{A}\boldsymbol{Y}\|_F^2+\frac{\alpha}{2}\boldsymbol{trace}\left(A^T A\right)+\lambda\sum_{i=1}^{N}\|\boldsymbol{y}_i\|_1, \quad (1)$$

Classification based on DL can be performed by training a classifier over the sparse training coefficients matrix $\boldsymbol{Y}$. The sparse representation models use inner products of instances that can be easily extended to kernel versions.

III. **RESULTS**

For each patient, we take 36 spatio-temporal profiles, 6 profiles by anatomical segment in the mid-cavity plane, according to the AHA (American Heart Asociation) representation. Radial strain curves in 2D speckle tracking echocardiography were analysed for the patient group and used as ground truth. Strain values were assessed by physicians in the medical reports and they allowed to label each profile as normal or abnormal (akinetic or hypokinetic cases). We take randomly 75% of the profiles cataloged as abnormal to conform one half of the training group. The other half has the same number taken randomly from the group of normal profiles. The parameter extraction procedure is applied over all the profiles. Different parameter combinations are used as input atoms to train the KSRDL algorithm with the following specification: Gaussian prior over the dictionary atoms, Non Negative Quadratic Problem in the sparse coding stage, a k-Nearest Neighbor (*knn*) classifier over the sparse codes and a RBF mapping function that replace the inner products in the DL model. Significant results are shown in Table 1 where classification based on SVM with a RBF kernel are also presented for comparisons. Results show that the best rate of classification is achieved when training vectors include the skewness (Sk) and the average curve (Cl) parameter with an accuracy about 94%.

Table 1: Accuracy obtained by different techniques

Test	SVM	KSRDL
Sk - Cl	93.50 ± 2.35	94.49 ± 1.59
Sk - Cl - Co	94.34 ± 1.42	94.06 ± 2.38
Sk - Mt	92.03 ± 1.36	92.59 ± 2.39
Sk - Mt - Cl	94.25 ± 1.38	93.81 ± 2.06
Sk - Mt - Cl - Co	94.32 ± 1.49	93.99 ± 2.19

IV. **CONCLUSION**

We presented a regional LV wall motion classification based on a parametric approach using Kernel DL. In this work we reduce significantly the length of the training vector representing each profile in parameters, consequently the training and testing times are reduced. Results show that skweness of TSICs plays an important role in the identification of wall motion abnormalities. Results are comparable with those obtained with SVM using a RBF kernel, with the advantage that DL model takes less atoms than support vectors used by the SVM model in the classification process.

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